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Interference Mitigation for Cyber-Physical Wireless Body Area Network System Using Social Networks

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ABSTRACT Wireless body area networks (WBANs) are cyber-physical systems that emerged as a key technology to provide real-time health monitoring and ubiquitous healthcare services. WBANs could operate in dense environments such as in a hospital and lead to a high mutual communication interference in many application scenarios. The excessive interferences will significantly degrade the network performance, including depleting the energy of WBAN nodes more quickly and even eventually jeopardize people's lives because of unreliable (caused by the interference) healthcare data collections. Therefore, it is critical to mitigate the interference among WBANs to increase the reliability of the WBAN system while minimizing the system power consumption. Many existing approaches can deal with communication interference mitigation in general wireless networks but are not suitable for WBANs because of ignoring the social nature of WBANs by them. Unlike the previous research, we for the first time propose a power game based approach to mitigate the communication interferences for WBANs based on the people's social interaction information. Our major contributions include: 1) modeling the inter-WBANs interference and determine the distance distribution of the interference through both theoretical analysis and Monte Carlo simulations; 2) developing social interaction detection and prediction algorithms for people carrying WBANs; and 3) developing a power control game based on the social interaction information to maximize the system's utility while minimize the energy consumption of WBANs system. The extensive simulation results show the effectiveness of the power control game for inter-WBAN interference mitigation using social interaction information. Our research opens a new research vista of WBANs using social networks.

INDEX TERMS Wireless body area networks (WBANs), inter-network interference mitigation, power control, game theory.

I. INTRODUCTION

In recent years, WBAN development has been driven by the needs to reduce the healthcare cost, and to support disease prevention and early risk detection. WBANs are operated around human bodies, using low power wireless technology to interconnect tiny sensors either implanted in or worn on human bodies. These devices enable continuously real-time remote monitoring of physiological signals. A typical WBAN system consists of a number of lightweight and miniature sensors, each featuring one or more physiological or physical sensors, such as electrocardiogram (ECG), electroencephalograph (EEG), electromyographic (EMG), blood PH, glucose, accelerometer and gyrometer, which can communicate with a network coordinator in a star topology of WBANs.

WBANs are cyber-physical system (CPS) that are designed to provide real-time health-care, emergency medical and personal entertainment services. The physical nature of WBANs lie in the fact that it operates on human body and requires sensing, control and Quality of Service (QoS). Some studies in cyber-physical WBANs system include a systematic design approach in [1] and model based engineering (MBE) approach [2]. A cyber-physical game controller for WBANs is proposed to broaden users' view and provide more realistic interaction experiences in [3]. The authors in [4] characterized the energy footprint of a cyber-physical security solution for WBANs and proposed a physiological signal based key agreement (PKA).

In this paper, we mainly focus on addressing the problem of the interference that degrades the system performance of the cyber-physical WBANs system. WBANs must function well even in a dense network environment, such as in a shopping center, a school or a hospital. However, one WBAN may interference with another if they are close to each other. The excessive interference called inter-WBANs interference will severely degrade the system's performance including depleting the system's power quickly. Especially, in many medical applications, the collected health data are critical and must be delivered to the data center reliably. Thus, the inter-WBANs interference must be dealt with in an appropriate manner. In a dense WBAN environment, each user carrying WBAN is more likely to be close to others, and they will interfere with each other due to using same frequency bands. The interference decreases the signal to interference plus noise ratio (SINR) and thereby cause throughput degradation and more packet losses, which could also consume the power of sensor nodes more quickly. It should be noted that the power is a scarce resource in WBANs due to the fact that most sensors are battery-powered.

The interferences among adjacent wireless networks have been extensively studied for wireless cellular networks such as in [5]–[11]. In these papers, analytical co-channel interference models are proposed and the methods based on coding or Media access control (MAC) are presented for the interference mitigation. A variety of game theory based approaches have also been investigated for the interference compensation in cellular networks [12]–[15]. However, WBANs are different from wireless cellular networks in the nature: Firstly, in WBANs, sensors nodes tend to be more dense in the body area; Secondly, the power control is more difficult due to the low-energy consumption requirements of WBAN nodes; Thirdly, the communication coverage of WBANs nodes is much shorter than mobile cellular phones; Last, the inter-WBANs interferences are closely related to the social activities of users carrying them. Considering these features of WBANs, in this paper, we propose a novel power control game based on the social interaction prediction to reduce the inter-WBAN interference without sacrificing the system's performance.

The transmission power control plays an important role in the interference mitigation problem in WBANs. Game theory has been applied to address the power control problem. In a cooperate power control game, as long as each node in the WBANs follows the game rules, a equilibrium solution can be reached, which is optimal for all individuals. The inter-network interference mitigation for WBANs has been studied in paper [16]–[18]. Based on a small random network graph, power control games are used to coordinate the power supply among the nodes. Due to the fact that WBANs are carried by human bodies, the inter-network interference occurs when people are close to each other. The interference is closely related to the social activities of people carrying WBANs. According to the social network theory, the activities of social nodes are not random but satisfy some certain distributions [19]. In a continuous time frame, some social interaction information such as state of social interaction may not change, as shown in Fig. 1. Fig. 1 shows an example of the social interaction information in three continuous time frames. The nodes in the figure present individuals carrying WBANs and the links mean the occurrence of social interaction such as chatting. Because the social interaction may last for some time, some interactions do not change in the next time period as marked by dashed arrows in the figure. It helps to improve the performance of the interference mitigation if the unchanged social interaction information is considered. Thus, the social interaction information will play an important role in inter-network interference mitigation. In this paper, both social interaction information and the movement of individuals are considered when a power game is used to mitigate the inter-network interference.

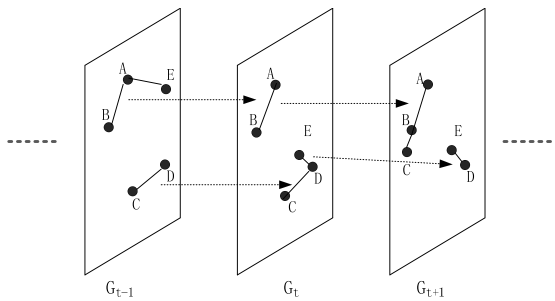

FIGURE 1. Illustration of the social interaction information in three continuous periods.

Our main contributions in this paper can be summarized as follows.

- We formulate the inter-network interference model based on social interaction information. Because people's interaction is not random but satisfies certain distribution, to better understand the interference scenario, we build a inter-network interference model for WBANs, in which the number of interference nodes for the WBANs satisfies power law distribution, a typical social network model.
- We give the probability density function (PDF) about the interference distance distribution. Due to the fact the distance between interference nodes is a key factor to the SINR, the PDF is important for the inter-network interference mitigation.
- We develop social interaction detection and prediction algorithms for people carrying WBANs.
- We design a cooperate power control game including social networks information to solve the inter-network

interference mitigation problem. We also validate the performance of the proposed power control game under social interaction scenarios.

The rest of this paper is organized as follows. In Section II, we present an overview of the related works. In Sections III and IV, we introduce the system design and power game formulation, respectively. We validated our designs in Section V, and conclusions are reached in Section VI.

II. RELATED WORKS

The WBAN is a cyber-physical system. Many researchers have put their attention on WBANs design [20]–[22]. Paper [20] proposes a usable and secure key agreement scheme for WBAN using biometric. A heartbeat driven medium access control scheme for WBAN is proposed in [21]. The authors in [22] propose BAND-Aide, a tool for CPS oriented analysis and design of WBANs. However, in these works the authors don't consider the interference between co-existing WBANs.

Scheduling mechanism can be used to reduce the communication interference [23], [24]. Paper [23] proposes a wireless link scheduling scheme under physical interference model. The authors of Paper [24] proposes an Intra-site scheduling for interference avoidance in LTE system. However, when WBANs are carried by each of people individually, it is challenging to schedule the transmissions among multiple WBANs. In the literature, there are few works on interference mitigation using scheduling for WBANs.

Media access control (MAC) based interference control has been studied for wireless networks [25], [26]. Paper [25] presents a MAC protocol that can achieve high throughput bulk communication for data-intensive applications. A cognitive MAC protocol using statistics channel allocation is proposed in paper [26] to coordinate the spectrum resources. Several centralized and distributed algorithms using power control have been proposed for wireless networks. In centralized approaches [27], [28], there is always a central coordinator which controls the medium access and transmission power so as to control the inter-network interference. For instance, in cellular network, the base station (BS) acts as a network coordinator which control the medium access and transmission power for each network node. In [29]–[31], the authors consider the inter-network interference mitigation for WLAN. However, these approaches are not suitable for the inter-network interference mitigation for WBANs. One reason is that the topology structure of WBANs is unique and is different from other types of wireless networks. The second reason is that the nodes in WBAN is low-power and energy-limited, so achieving energy efficiency is more important in WBANs than in other wireless networks.

Game theory has been applied to solve the inter-network interference mitigation problem for wireless network [16], [32], [33]. In [16], game theory based distributed power control algorithms, named ADP and MADP algorithms, are introduced both for single channel and multiple channel wireless networks. In [33], game theory is used to solve the flow control problem for variable rate traffic at a bottleneck node. The authors in [32] use game theory to do both channel allocations and power control for interference mitigation in wireless networks. They formed a cooperate game in which each node can be viewed as a rational player and different users adjust their transmission power levels to maximize system utility in a distributed fashion. However, they either consider a random network topology or an uniform network topology, which is not the case for the inter-WBANs interference in a social interaction scenario. The authors in paper [17], [18] propose using power control game to mitigate the inter-WBAN interference. However, they do not consider the social interaction of people carrying WBANs nodes, which have significant impact on inter-WBANs interferences.

Besides the above interference mitigation techniques that are all above the physical layer, the communication interference can also be reduced by physical layer techniques. For example, the authors in [34] proposed a hybrid MMSE and interference cancellation scheme. Due to the mobility of human beings who carry the WBANs, the inter network interference may change with individuals' social activities. However, it is a challenging task to monitor people's social interaction. Bluetooth technology is used in paper [35] to detect social interaction. However, the results are not accurate in this method. In our previous work [36], an approach of using acoustic signal to detect nearby nodes is proposed. The distance detected by the acoustic waves is more accurate than the Bluetooth method. To facilitate the theoretical analysis, we also model the inter-network interference of WBANs based on the social interaction information. A PDF of the distance distribution of the interference links is derived. The result is validated through computer simulations. We also formulate a cooperate power control game to minimize the energy consumption while keeping the system's performance. The results are compared to the scenarios in random network topology and uniform network topology.

III. SYSTEM DESIGN

A. INTER-WBANs INTERFERENCE

In a WBAN system, The body sensors can communicate the body central node via Bluetooth, ZigBee, or IEEE 802.15.6. The central node can communicate with the mobile phones through Bluetooth because most smart phones have built-in Bluetooth transceivers. The mobile phone will forward the collected data to the internet server via WiFi or cellular network. The control center or the remote users are able to access the sensor measurements and control the WBANs through the internet. The system diagram is shown in Fig. 2.

In this paper, we consider the inter-network interference mitigation for WBANs based on social interaction information. We assume that a TDMA based media access control (MAC) control scheme is applied to control message scheduling within a WBAN and thus the intra-network collision thus can be avoided. However, nearby WBANs will interfere each

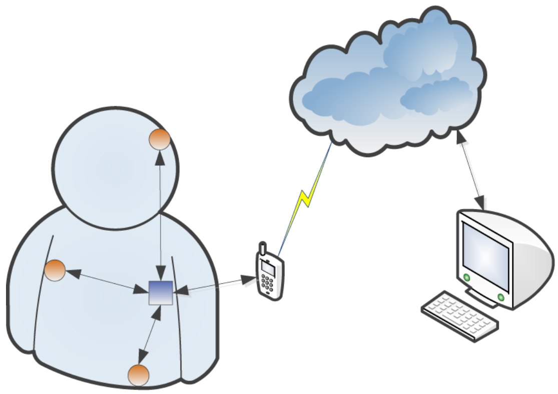

FIGURE 2. System diagram for WBANs.

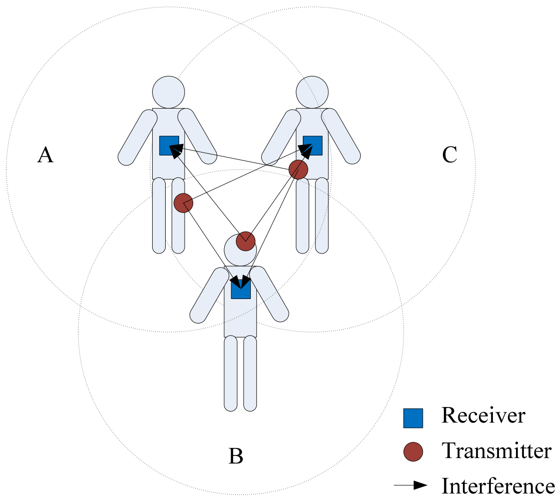

FIGURE 3. Inter-network interference problem for WBANs.

other because their communication range may overlap. See Fig. 3 as an example. Each individual user carries a WBAN, which consists of a central node (receiver) and several sensor nodes (transmitters). These WBANs may interfere with each other during the social interaction period because people carrying them are close to each other. The arrows in Fig. 3 show the inter-network interference links in WBANs.

In our system, the body sensors send their collections to the central nodes through IEEE 802.15.6 or ZigBee. The mobile phone then forwards the collection from central nodes to the health data center or remote users via WiFi or cellular network. It is assumed that the central node does have an extra gateway interface that bridges sensor nodes and smartphones.

A geometric social network $G(V, E)$ with radius r is a graph with node set V in a metric space and edge set $E = \{\{u, v\} | (u, v \in V) \wedge (0 < \|u - v\| \leq r)\}$, where $\|\cdot\|$ is an arbitrary distance norm in this space. Thus, two nodes are adjacent if the distance between them is at most r. The distance between two points (x_1, y_1) and (x_2, y_2) is calculated in the l_2 norm by $\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$. In this paper, we build the network model based on the social interaction model.

In a system that contains many WBANs, their transmission ranges may be overlapped, which cause the interference. In this paper, we model the system in a scale free network in which the nodes' degree should satisfy a power law distribution. In the scale free network, the distribution of the nodes' degree does not change with the size of the network. By power law distribution, the fraction of the nodes that have k neighbors, denoted by $P(k)$, is proportional to $k^{-\alpha}$ for a large value of k, or

$$P(k) \propto k^{-\alpha} \tag{1}$$

where α is a positive constant value. The typical value of α in social network is in the range of [2], [3]. If we define a coefficient C, the probability that a node has $deg(\kappa)$ neighbors, where $deg(\kappa)$ follows the power law distribution

$$\text{prob}(deg(\kappa) = k) = Ck^{-\alpha} \tag{2}$$

where C is a constant and $C \sum_{k=1}^{\infty} k^{-\alpha} = 1$.

In this paper, to investigate how the social interaction information will help the interference mitigation, we propose to use social networks as a tool to build a social interaction network (SIN) to model the social interactions among people based on their location information. In SIN, if two nodes are close to each other, we make an edge between them. Next, based on the SIN, we know that some nodes' communication ranges are overlapped and they interfere with each other. We formulate a power control game to maximize the system's performance while minimizing the total power consumption.

Algorithm 1 Social Contact Network Consisting of WBANs

Require: Number of WBANs N, radius of a WBAN r, grid size of the graph L and power law exponent α
Ensure: Social contact network G
Set up a grid G with length L
Randomly place N' $(1 < N' < N)$ nodes in the grid
for i from N' to N **do**
    Randomly choose L position in the grid to add a new node i
    for j from 1 to L **do**
        Calculate the fitting coefficient f_j if node i is placed in position j
    end for
    Put node j at the position whose fitting coefficient is the biggest among the L fitting coefficients
end for
Add links between any two WBANs if they are adjacent
Output the social contact network G

The proposed algorithm of building a SIN that contains many WBANs is shown in Algorithm 1. First, we set values for the number of WBANs in the graph, the radius of each WBAN r, the size of the grid in the graph L and the power law exponent α. Then, we randomly put N' nodes in the graph.

Next, we put nodes into the graph one by one. For each node, we select L potential positions and finally place the node to the place where the fitting coefficients is the biggest among the L positions. After placing all the N nodes in the graph, the algorithm outputs the social interaction graph in which an edges exists if the two nodes are close to each other.

B. DYNAMIC SOCIAL INTERACTION DETECTION

In our proposed design, the social interaction information will be used to reduce the inter-network interference for WBANs. However, it is challenging to detect and measure the social interaction in the social networks. Nowadays, most people have mobile phones and use them in daily lives. In particular, the mobile phones have more and more sensors that could sense the context data and deliver them among the networks. For example, most of the mobile phones have speakers and microphones which could send and receive acoustic waves. So it is convenient to exploit the acoustic signal processing techniques along with the Bluetooth technology to measure the physical distance among the mobile phones which play as a gateway of WBANs.

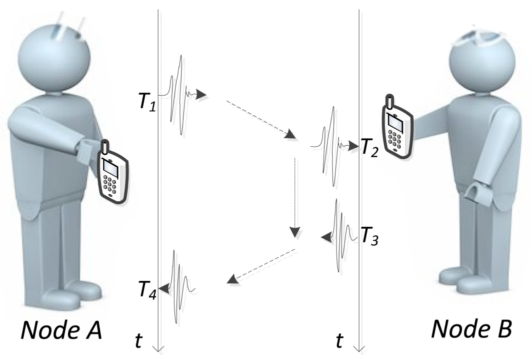

FIGURE 4. Dynamic social interaction detection.

In this paper, we proposed a social interaction detection strategy that detects nearby WBANs and the distance among them using both Bluetooth and acoustic wave technology. Bluetooth is a proprietary open wireless technology standard for exchanging data over a short distance. In most cases, the effective communication range of the Bluetooth signal is 10 meters. The acoustic wave could be sent and received by mobile phones with speakers and microphones. One device sends an acoustic wave and wait until it receives the acknowledge back. Then the two-way distance could be estimated by the waiting time multiplying the speed of acoustic wave in the air. As shown in Fig. 4, at time T_1, node A broadcasts an acoustic wave. Node B receives the wave at time T_2 and replies the wave at time T_3. If node A is able to get an acoustic wave back at time T_4, the social interaction is detected and also the distance between them can be estimated by

$$\begin{aligned} D &= S \times \frac{(T_2 - T_1) + (T_4 - T_3))}{2} \\ &= S \times \frac{(T_4 - T_1) - (T_3 - T_2))}{2} \end{aligned} \tag{3}$$

where S is the propagation velocity of acoustic sound in air, $T_3 - T_2$ is a constant. The procedure of the proposed nearby WBAN nodes detection and distance measurement is as follows: (i) The mobile phone (WBAN gateway) opens Bluetooth to search the nearby devices that have Bluetooth enabled. (ii) If nearby nodes are detected, the node records their ID and goes to next step. (iii) The mobile phone runs acoustic meters [36] to send a acoustic wave and wait until the acknowledge is received. Then the the delay time multiplying the propagation velocity of the acoustic wave in the air is the estimation of two-way distance between the two devices.

The social interaction among people will be detected even if two people only have a short conversation. If they keep stay closely to each other for a long time, their interaction will be detected for multiple times, which is not energy efficient. If we can predict the social interactions among individuals within a certain period, the social detection will consume less energy by skipping Bluetooth broadcast process. In addition, the predicted information will be helpful to the power game design for interference mitigation. In the paper, we proposed a four-state dynamic social interaction prediction algorithm, shown in Fig. 5. It is worth noting that there are other potential predictors such as static predictor, last time predictor and statistic prediction models. The static predictor always makes the same predictions while the last time predictor makes prediction only based on the last time state. However, both of them achieve worse performance than our proposed four-state prediction algorithm. In the future, we may further investigate some more complex static predictors such as Markov Chain predictive models.

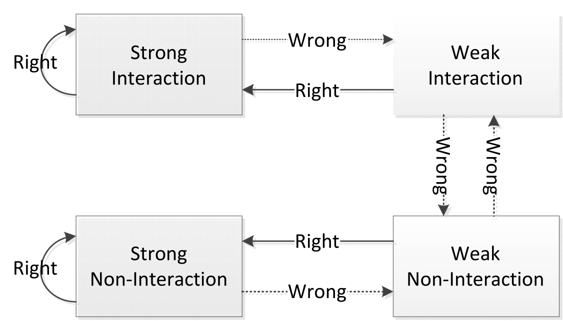

FIGURE 5. Social interaction prediction.

As shown in Fig. 5, the social interaction predictor has four states: *Strong Interaction*, *Weak Interaction*, *Strong Non-Interaction* and *Weak Non-Interaction*. The predictor outputs *Yes*, meaning the occurrence of a social interaction, if it is in the first two states; The predictor outputs *No*, meaning no social interactions if it is in the last two states. The predictor changes its states to others based on whether the prediction is right or not. For example, if the predictor is in the state of *Strong Interaction* at time t, then it predicts there will be interaction at time $t + 1$. If the interaction is detected at time $t + 1$, the prediction is correct and the predictor remains in the state of *Strong Interaction*. If not, the prediction is wrong and the predictor changes to the state of *Weak Interaction*.

C. CHANNEL GAIN MODEL FOR INTERFERENCE LINKS

The strength of the interference signal is a function of the distance between the transmitter and the receiver. The interference channel gain q_{ji} can be obtained before using power control to mitigate the interference. When we consider the interference among the WBANs, where their communication ranges may overlap to cause interferences, the WBAN topology has a significant impact on the total interference level. Base on [17], the channel gain q_{ji} of the link from person j's transmitter to person i's receiver is calculated by

$$q_{ji} = d_{ji}^{-4} \tag{4}$$

in which d_{ji} is the distance between person j's transmitter to person i's receiver.

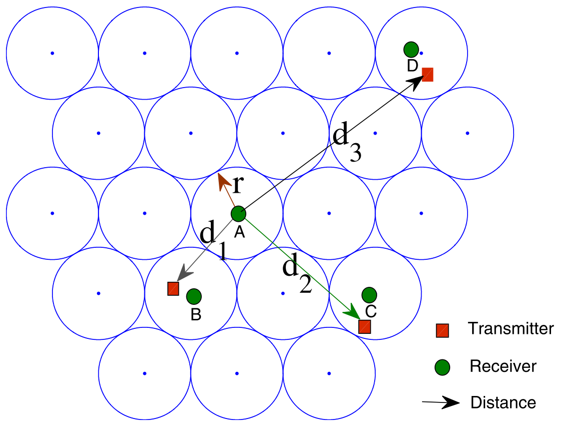

FIGURE 6. Network topology.

As shown in Fig. 6, node A is the coordinator of tagged WBAN, and there are six WBANs which are closest to it. We call these six WBANs as tier-1 neighbors. Node B belongs to tier-1. The WBAN nodes outside tier-1 and closest to tier-1 belong to tire-2. In this case, node C belongs to tier-2. The WBANs outside tier-2 and closest to tier-2 nodes belong to tier-3. Node D is outside tier-2 and belongs to tier-3. Because of the low energy requirements and short communication range of WBAN nodes, in this paper we do not consider the interference from tier-3 and even further.

Based on the topology shown in Fig. 6, the distance from the center of any WBAN in tier-1 to the center of tagged Node A D_1 is $2r$, and the distance from the center of any WBAN in tier-2 D_2 is either $2\sqrt{3}r$ or $4r$. However, the interference are from the links between one person's transmitter and other receivers. For example, when the receiver of person A receives the message sent from person B's transmitter to person B' receiver, and the transmitter of person A is sending message to person A's receiver at the same time, then a collision occurs and the link from B's transmitter to A's receiver causes the communication interference. If we know the distance between B's transmitter and A's receiver, we can estimate the interference channel gain. Assuming that person B's transmitter is randomly placed within r centered to B's receiver, we can compute the Cumulative Distribution Function (CDF) of the distance d_1. Through the same process, we can get the CDF of the interference distance d_2 from tire-2 to the tagged WBAN. The CDFs for d_1 and d_2 can be written as

$$\mathrm{CDF}_{d_1}(z) = \begin{cases} 0 & z < r \\ \frac{S_1(x_1,y_1)+S_1(2r-x_1,y_1)}{\pi r^2} & r \le z < 2r \\ \frac{S_1(x_1,y_1)+S_2(x_1-2r,y_1)}{\pi r^2} & 2r \le z < 3r \\ 1 & z \ge 3r \end{cases} \tag{5}$$

$$\mathrm{CDF}_{d_2}(z) = \begin{cases} 0 & z < (2\sqrt{3}-1)r \\ \frac{S_1(x_2,y_2)+S_1(4r-x_2,y_2)}{\pi r^2} & (2\sqrt{3}-1)r \le z < 4r \\ \frac{S_1(x_2,y_2)+S_2(x_2-4r,y_2)}{\pi r^2} & 4r \le z < 5r \\ 1 & z \ge 5r \end{cases} \tag{6}$$

in which

$$\begin{aligned} x_1 &= \frac{z^2+3r^2}{4r} \\ y_1 &= \frac{\sqrt{-z^4+10z^2r^2-9r^4}}{4r} \\ x_2 &= \frac{z^2+15r^2}{8r} \\ y_2 &= \frac{\sqrt{-z^4+34z^2r^2-225r^4}}{8r} \\ S_1(x,y) &= z^2 \arctan\frac{y}{x} - xy \\ S_2(x,y) &= (\pi - \arctan\frac{y}{x})r^2 + xy. \end{aligned} \tag{7}$$

When the CDFs of d_1 and d_2 are known, we can calculate the Probability Density Functions (pdf) for d_1 and d_2 by formulation of $\mathrm{pdf}(x) = \frac{\mathrm{d}}{\mathrm{d}x}\mathrm{CDF}(x)$. Fig. 7 plot the CDFs of the distance d_1 and d_2 with $r = 0.5$. The validity of the CDFs is also cross-checked using Monte Carlo simulation. There are 100 000 randomly generated transmitters in tier-1 and tier-2 within r to the center in the simulation. From the figures it is observed that the theoretical analysis of the CDF of the interference distances matches with the Monte Carlo simulation results. Therefore, in the following studies, we use the derivative of the CDF, which is PDF, to generate the interference distance values.

According to (3), the interference channel gain q_{ji} is the exponential function of the distance d_{ji}, which is the distance from the node j's transmitter to node i's receiver. In our following studies, we estimate the interference power by the PDFs of d_1 and d_2.

IV. POWER CONTROL GAME

In this section, we propose a power control game to do the inter-network interference mitigation for WBANs. Because the WBANs are battery-supported, it is critical to reduce the

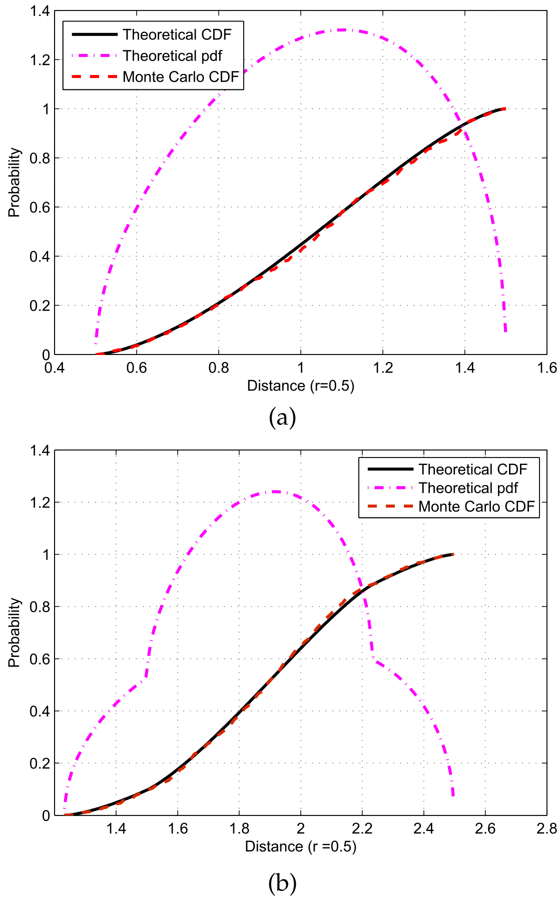

FIGURE 7. Theoretical analysis vs. numerical results. (a) Tier-1. (b) Tier-2.

energy consumption of WBAN system, prolong its lifetime and enhance the system's reliability. Therefore, the goal of the power control is to maximize the network utility while minimizing the power consumption.

A. OPTIMIZATION PROBLEM

We consider a scenario in which some of WBANs are close to each other. Because their transmission ranges may overlap, they could interfere with each other. As shown in Fig. 6, we assume that a TDMA based Media Access Control (MAC) scheme is used within the WBANs to avoid the intra-network collision. Due to the block fading based wireless channel where the channel gain is constant within each block, we also assume the channel gains of each transmitter and the interference gains are fixed. Assuming there is a network graph that consists of N WBANs, and there are interference among them if their transmission ranges are overlapped with each other. Then node i's SINR can be expressed as

$$r_i = \frac{q_{ii}(\hat{d}_{ii})p_i}{\frac{1}{B}\sum_{j\neq i} q_{ji}(\hat{d}_{ji})p_j + n_0} \tag{8}$$

where B is bandwidth. p_i and p_j are the transmission power of node i and node j. n_0 is the white noise power at receiver i. q_{ii} and q_{ji} are the channel gain between transmitter i and receiver i, and the channel gain between transmitter j and receiver i, respectively. In this paper, we define the utility as $u_i = \log(r_i)$, then the system utility is

$$U = \sum_{i=1}^{N} \log(r_i). \tag{9}$$

In a social interaction network, the social interactions usually last some time duration. If each individual carries a WBAN, there will be inter-network interference due to the overlapping of their communication ranges. In this paper, based on the prediction of the interference distances, we optimize the transmission power of the node to mitigate the interference. For example, if a social interaction is detected between nodes i and j at time t and the interference distance is d_0, then the interference distance at the next time $t+1$ will be

$$\hat{d}_{ij}^{t+1} = d_{ij}^{t}. \tag{10}$$

In this paper, we want to maximize the system's performance while minimizing the total power consumption. The optimization problem can be written as

$$\begin{cases} \max \sum \log(r_i) \\ \min \sum p_i \end{cases} \tag{11}$$

where $0 \leq p_i \leq P$, for each transmitter, P is the maximum transmit power. Then we apply game theory to solve the power control problem to maximize the system's utility while minimizing the total power consumption. The power control game is formulated by (i) The N transmission links between the transmitters and the corresponding receivers in the N WBANs acting as N players in the game. (ii) The transmission power for the N players should be in the range of 0 to P. (iii) Each player in the game are assumed to be cooperative, which means they correctly follow the algorithm. (iv) The price for player i if the transmission power is p_i is defined as

$$\pi_i(p_i, p_{-i}) = w_1 \times r_i - w_2 \times p_i \tag{12}$$

where the price function for each player is the difference between weighted utility and weighted power. For simplicity, we can set $w_1' = 1$ and $w = w_2' = \frac{w_2}{w_1}$. Then the above formula can be written as

$$\pi_i(p_i, p_{-i}) = r_i - w \times p_i \tag{13}$$

in which the weight w can be set according to the WBANs' wireless channel state, power state and different constraints on power and Quality of Service (QoS) requirements.

B. POWER CONTROL GAME ALGORITHM

According [17], there exists a Nash Equilibrium in the power control game defined above if and only if $p_i^* = \arg\max_{p_i} \pi_i(p_i, p_{-1})$ for all player i and for all q. The proof is as follows. According to [37], if the power control game has non-empty compact convex subsets of an Euclidean space for power p_i and the price π_i are continuous, there must be a pure strategy Nash Equilibrium. For player i, we have

$$\frac{\partial \pi_i(p_i, p_{-i})}{\partial p_i} = \frac{q_{ii}(\hat{d}_{ii})}{\frac{1}{B}\sum_{j\neq i} q_{ji}(\hat{d}_{ji})p_j + q_{ii}(\hat{d}_{ii})p_i + n_0} - w = 0 \quad (14)$$

which can be solved for all p_i, to get

$$p_i = \frac{1}{w} - \frac{\frac{1}{B}\sum_{j\neq i} q_{ji}(\hat{d}_{ji})p_j + n_0}{q_{ii}(\hat{d}_{ii})}. \quad (15)$$

It can be easily shown that for all $p_i \in [0, p']$, π_i is strictly non-decreasing and then strictly non-increasing for $p_i \in [p', P]$, where $p' = \frac{\frac{1}{B}\sum_{j\neq i} q_{ji}(\hat{d}_{ji})p_j + n_0}{q_{ii}(\hat{d}_{ii})}$. Thus π_i is a strictly concave function. Therefore the existence of the Nash Equilibrium in the power control game is proved.

We have proved the existence of a Nash Equilibrium in the power control game defined above. If each user in the game gets the optimal transmitting power, the system has reached to a point that balances the overall transmission power and the system utility. As shown in Equation (15), the optimal power for each player is based on the distance between the users. Therefore, our social interaction detection is based on distance measure between users. If the interactions are not detected correctly, the system will not reach to the balance point. In the future, we may develop a validation scheme that detects the social detection errors.

Algorithm 2 Power Control Game Algorithm

Require: Each player $i \in N$ is initialized with a random transmission power and price $p_i(0) \in [0, P]$ and $\pi_i(0) \geq 0$

Ensure: Optimal transmitting power for all players in the game $\{p_1, p_2, \ldots, p_N\}$

1: Distance update: At each turn, the estimated distance equals to the previous distance if social interactions are detected. Otherwise, update the distance by interference distance detection
2: Power update: At each turn, player i updates its power according to $p_i(t) = W_i(p_{-i}(t^-), \pi_{-i}(t^-))$
3: Price update: At each turn, player i updates its price value according to $\pi_i(t) = \Pi(p_i(t^-))$
4: **if** all p_i don't change in the last continuous five turns **then**
5:     Ouput $\{p_1, p_2, \ldots, p_N\}$
6: **else**
7:     Go to Distance update
8: **end if**

In the proposed power control game, each player has an initial transmission power and the players are able to update their powers and prices at each turns. When the transmission power of all the players do not change, the algorithm stops and outputs the optimal transmission power for all the transmitters. The algorithm of the power control game is shown is Algorithm 2.

Not only the powers and prices generated in a distributed fashion in the power control game introduced above, but also the each player only needs to acquire very limited information. Note that the power and price update function can be written as follows.

$$W_i(p_{-i}(t^-), \pi_{-i}(t^-)) = \frac{1}{\sum_{j\neq i} \pi_j(t^-) q_{ji}(\hat{d}_{ji})} \quad (16)$$

$$\Pi(p_i(t^-)) = \frac{1}{\sum_{j\neq i} p_j(t) q_{ji}(\hat{d}_{ji}) + Bn_0} \quad (17)$$

where t^- represents the next time moment. From these equations, we can find that the player i needs to know the following information to implement the update, (i) its own channel gain q_{ii}, current SINR r and own utility u_i. (ii) The nearby players channel gain q_{ji}, $j \neq i$ & $i, j \in N$.

The nearby channel gains account for only $1/N$ of the total channel gains in the system, each player does not need to know the other gains. Due to each player announces only a single price value, the number of prices scales linearly with the size of the WBANs. What's more, because of the short communication ranges in WBANs, only the nearby transmitters cause the interference. If the two players are far away form each other, the interference is very small and can be ignorable.

The power game design is based on the social interaction information (i.e., distance between users). The social interaction information provided us with the changes of network topology. In the proposed interference mitigation scheme, we use 4 state predictors to predict the topology change based on this information. The advantage of this approach is the adaptation to the network topology change and to reduce the frequency of topology information collections. Compared with traditional game control approach, the communication overheads have been significantly reduced. In the paper, the proof of the existence of a Nash Equilibrium of the proposed power control game uses the social interaction information.

V. SIMULATION RESULTS

In this section, we conduct the simulation and demonstrate the performance of the proposed algorithms.

A. NETWORK MODEL

We simulate a network in a 20 m × 20 m square area. The simulation setting are: $P_i/n_0 = 40$ dB and $B = 128$. Individuals are placed in this area according to the procedure introduced in Section III to SIN, which follows a power law distribution. Each person carries a receiver and the transmitters are placed in a 1 m × 1 m circle centered around the corresponding receivers.

Fig. 8(a) shows an example of the generated networks of WBANs at time t, which has 40 WBAN nodes. From time t to time $t + 1$, we make 10% WBAN nodes in the network to randomly move, and we get Fig. 8(b) as the network graph for time $t + 1$. In the two figures, the circles are the areas that taken by individuals. The centers are receivers and the

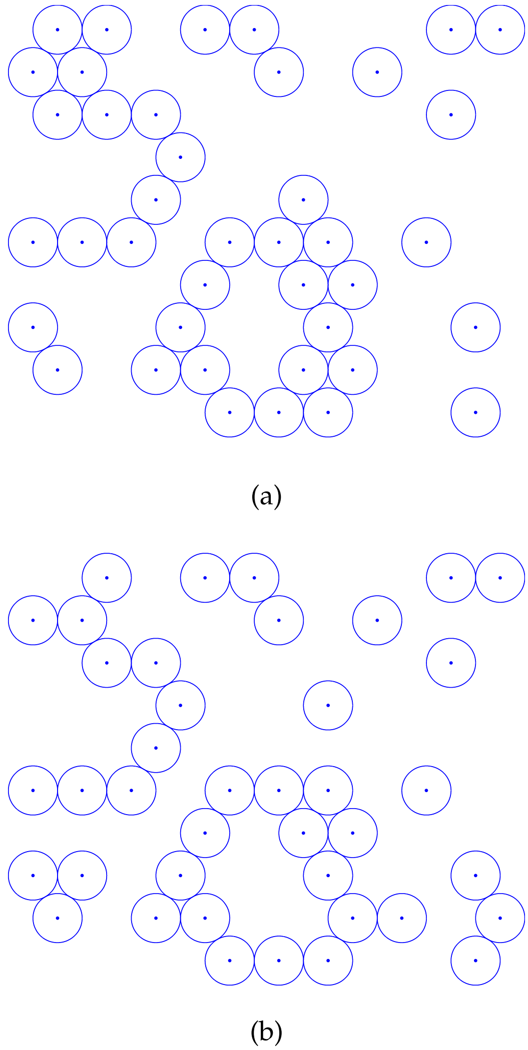

FIGURE 8. **Network topology for WBANs. (a) Network of WBANs at time t. (b) Network of WBANs at time $t+1$.**

transmitters are randomly placed in the corresponding circles. From time t to time $t+1$, only 10% nodes could move. Then we can find from the figures that the two networks has many common interference links.

B. PERFORMANCE EVALUATION

First, we examine the convergence of the power control game with 40 nodes and each with utility $u_i = \log(r_i)$. Fig. 9 shows the convergence of the powers for each node under the power control game starting with random initializations.

Next, we show the performance of using power control game from time t to time $t+1$. We know that most (90%) WBAN nodes do not change from t to $t+1$, we expect that the convergence in the power control game at time $t+1$ to be much faster than that at time t, which is shown in Fig. 9. In Fig. 9, each curve corresponds to the power for one user. At the beginning, each user is initialized to a random transmitting power, and then it updates the power according to Equation (16). The users' price will be updated as shown in

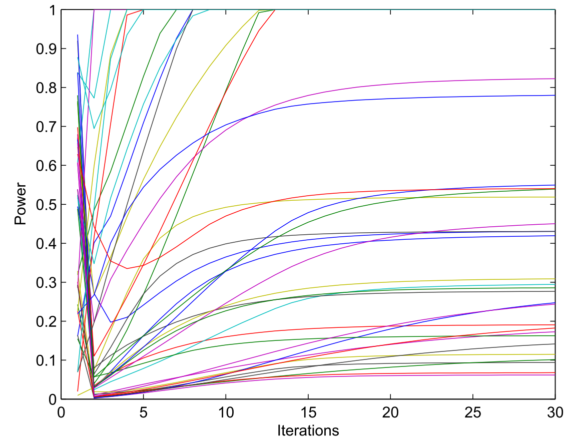

FIGURE 9. **Convergence of the power with a random initiation.**

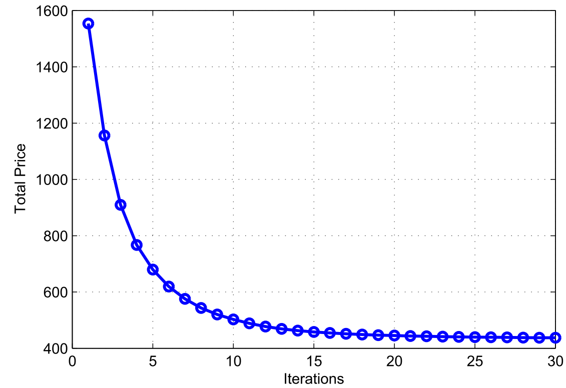

FIGURE 10. **Convergence of the price with a random initiation.**

Equation (17) when their transmitting powers have changed. All users in the game keep updating their power and price until their powers do not change. The convergence of the total price is shown in Fig. 10. The results of the power control game at time $t+1$ are shown in Fig. 11. It should be noted that the power control game converge more quickly compared to that at time t, which demonstrates the advantage of using social interaction information in inter-WBANs interference mitigation.

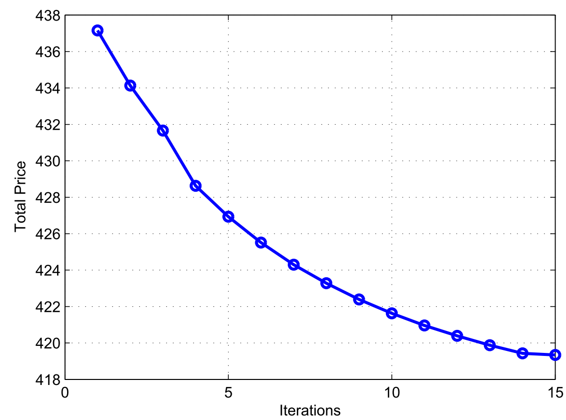

FIGURE 11. **Convergence of the price at $t+1$ from time t.**

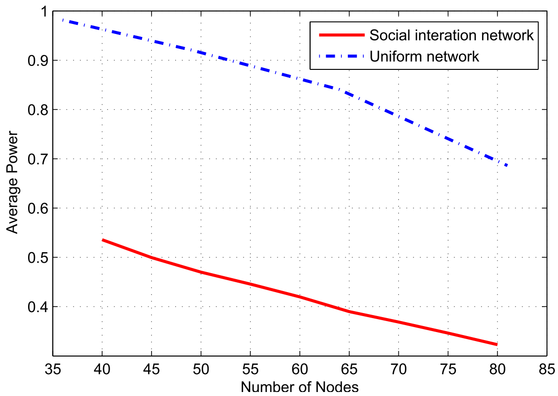

FIGURE 12. Average power as a function of the number of nodes in the network.

Then, we examine the performance of the power control game with the number of the nodes increasing from 40 to 80. Fig. 12 shows the nodes' average power is a function of the number of the nodes in the network. From the figure, we find that the average power decreases when the network contains more nodes. That is because if there are more nodes in the network, the interference increases and most of nodes need to reduce their power to reduce the interference according to the power control game. Fig. 13 shows the total utility is also a function of the number of nodes in the network. It is observed that, in the power control game, the total utility of the network is increased when there are more nodes in the network.

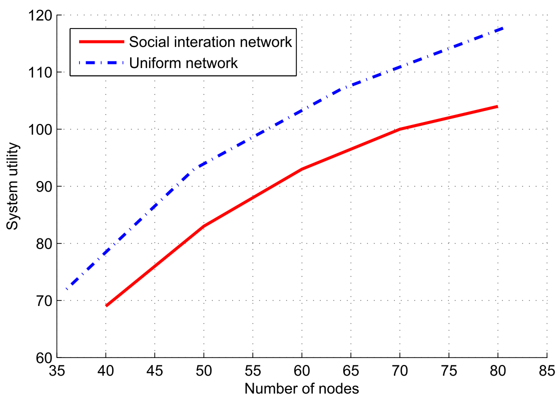

FIGURE 13. Total utility as a function of the number of nodes in the network.

Next, we apply the power control game in the uniform interaction network topology that contains the same number of nodes. The dashed line with squares in Figs. 12 and 13 show that the average power and total utility are closely related to the number of nodes in the network, respectively. It is also observed that the SIN topology save nodes' power by 50% by sacrificing only about 12% of system utility, which outperforms the one in uniform topology where no social interaction patten is considered. The proposed power control game is a distributed interference mitigation scheme. Each user in the game decides its transmitting power based on the information it collected. The algorithm will run on the sensors according to the power updating function of Equation (16). Therefore, the time complexity of the algorithm is $O(1)$.

We also study the effectiveness of social activity prediction in the proposed social information based power control game. A four-state predictor as shown in Fig. 5 is used to estimate the activity of the WBANs' users at next moment. Compared with the existing scheme in [17] which requires frequent distance update when the person carrying WBANs move, our scheme can achieve the better performance even under the same overheads by an effective social interaction prediction. As shown in Fig. 8(a) and (b), we allow 10% WBAN nodes move and apply our scheme for social interaction prediction in the scenario. We compare our scheme with the one without social predictions (i.e. [17]). Fig. 14 shows the total price reduced up to 7% by using social information when 90% of these node movements are predicted accurately. In the scheme without using social interaction prediction, since the people's social activities are changed dynamically. The WBAN system has to report the network topology changes and update the transmission power frequently, which is energy-intensive and may not be realistic. Our proposed social information based approach can reduce the frequency of the report and power update, and thus reduce the communication overheads. Even under the same frequency of the report and update, our proposed scheme can achieve more optimal power price.

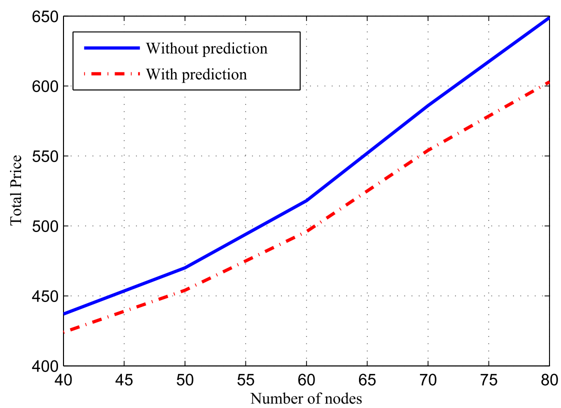

FIGURE 14. Total price with difference number of nodes in the network.

C. MIT REALITY DATASET

In the above, we evaluate the performance of the proposed social information based power control game based on the simulated contact network. In this section, we further evaluate the performance of the prosed algorithm based on the real social contact dataset. The Reality Mining project was conducted from 2004–2005 at the MIT Media Laboratory [38]. The Reality Mining study following ninety-four subjects using mobile phones pre-installed with several pieces of software that recorded and sent the researcher data about call logs, Bluetooth devices in proximity of approximately five meters and other context information. In the Reality Mining project, when a Bluetooth device conducts a discovery scan, other

Bluetooth devices within a range of 5–10 meters respond with their unique information, such as user defined name, the device type, and MAC address. When a subject's MAC address is discovered by a periodic Bluetooth scan performed by another subject, the two devices are 5–10 meters close to each other.

Then we assume that the ninety-four individuals are in a area of 30 meters by 30 meters, and the distance between two individual who have contact is a random number in the range from 1 meter to 10 meters. The communication range of the WBANs is 10 meters and the transmitter is located within 2 meters from its corresponding receivers for each WBAN. Fig. 15 shows the average power and system utility for six continuous times. The number of contacts are {95, 153, 157, 14, 26, 107} for these time moments. The results show that when the contact rate is higher, which means people are closer to each other, both the average transmission power and system utility are lower. Due to the limitation of acquiring large set of real social data, our studies are more focused on the theoretical analysis and model based approach.

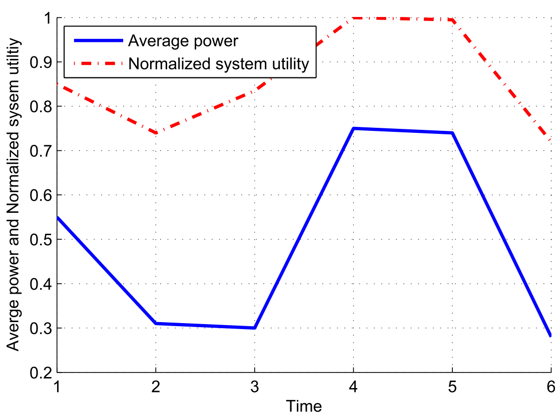

FIGURE 15. Average power and system utility for MIT reality dataset.

VI. CONCLUSION

In this paper, we have presented a social interaction information based power control game for inter-WBANs interference mitigation for cyber-physical WBANs system. Unlike the previous works, our game is designed based on social interaction detection and prediction, which considers the unique social interaction features of cyber-physical WBANs system. Firstly, we built the interference model based on social interaction information. Secondly, we model the social interaction and presented the PDF of the network interaction distances. Monte Carlo simulations are used to verify correctness of our proposed model. Thirdly, we applied game theory to control the WBANs' transmission power effectively in order to mitigate the interference. We proved the existence of the Nash Equilibrium in the power control game and gave the power update and price functions. The effectiveness of the proposed algorithm are demonstrated through expensive simulations and MIT reality Dataset. Our future work will focus on designing more effective MAC protocol that works with the proposed approach in order to further mitigate the inter-WBANs interference.

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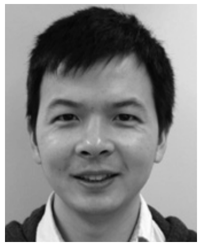

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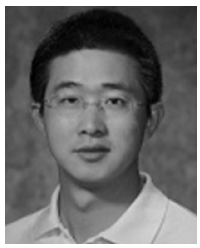

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